On Graph Features of Semantic Web Schemas

Yannis Theoharis, Yannis Tzitzikas, Dimitris Kotzinos, and Vassilis Christophides

***Abstract*— In this paper, we measure and analyze the graph features of Semantic Web (*SW*) schemas with focus on *power-law* degree distributions. Our main finding is that the majority of *SW* schemas with a significant number of properties (resp. classes) approximate a *power-law* for total-degree (resp. number of subsumed classes) distribution. Moreover, our analysis revealed some emerging conceptual modeling practices of *SW* schema developers, namely: a) each schema has a few focal classes that have been analyzed in detail (i.e., they have numerous properties and subclasses) which are further connected with focal classes defined in other schemas, b) class subsumption hierarchies are mostly unbalanced (i.e., some branches are deep and heavy, while others are shallow and light), c) most properties have as domain/range classes that are located high at the class subsumption hierarchies and d) the number of recursive/multiple properties is significant. The knowledge of these features is essential for guiding synthetic *SW* schema generation, which is an important step towards benchmarking SW repositories and query languages implementations.**

***Index Terms*— Semantic Web, power-laws, conceptual schemas morphology**

I. Introduction

A great number of *Semantic Web* (*SW*) schemas expressed in either *RDFS* [1] or *OWL* [2] has been developed during the last years. A *SW* schema can be viewed as a directed labeled graph where nodes are classes or literal types and arcs are properties. In this paper, we are interested in studying the morphology of real *SW* schemas based on the graph features they exhibit.

A main feature that characterizes graphs is the degree distribution. The Internet topology [3], the *WWW* [4], [5], as well as the call graph [6] have been observed to exhibit a *power-law* distribution for their in- and out-degrees. In our context, we need to analyze *SW* schema graphs whose structure is of different nature than the graphs already studied in the literature. In particular, according to the *RDF/S* [1] or *OWL* [2] specifications, in these graphs we have a) arcs representing subsumption relationships among classes, and b) arcs representing relations between classes (e.g. *has_a*) or attributes (e.g. *title*), collectively called properties. Hence, for each *SW* schema we essentially need to study two graphs that have the same set of nodes (i.e., classes or literal types), namely, the *subsumption*, and the *property* graph.

It would be interesting to investigate whether the property graph exhibits a *power-law* degree distribution. Examining the distributions involved in the subsumption graph could provide additional hints about the morphology of *SW* schemas. Specifically, we investigate *power-law*s on two different functions of a *DRV* (Discrete Random Variable) X. The first, called *Complementary Cumulative Density Function* (*CCDF*), i.e., $P(X \geq x)$, measures the frequencies of X values, while the second, denoted by *VR* (*Value vs Rank*), measures the relationship between the $i-th$ biggest X value and its rank (in descending order), i. Regarding the property graph, it should be noted that it may contain self-loops (e.g., recursive properties) and multiple arcs (i.e., two classes may be connected by more than one property).

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In our study, we mainly focus on the core *RDFS* [1] features which are also exploited by *OWL*. This decision is motivated by the fact that the majority of available *SW* schemas rely on the *RDFS* specification (according to [7], 85.45% relies on *RDFS*, while 14.55% on *OWL*). We additionally take into account *OWL* expressions, such as *unionOf*, *intersectionOf*, *someValuesFrom* and *allValuesFrom*, that impact the features of the underlying property and subsumption graphs.

Furthermore, we study the features of individual[1] *SW* schema graphs instead of the *universal SW graph* aggregating all *SW* schemas. This is motivated by the fact that the statistical analysis of individual *SW* schema graph features is essential to synthetically generate realistic *SW* schemas. Such a detailed analysis of individual *SW* schemas is not provided in [8], which essentially analyzes the aggregation of all DAML library ontologies. For instance, they found that the total-degree (i.e. in- plus out-degree) *CCDF* approximates a *power-law* with exponent 1.48. In our work, we have found individual schemas that approximate a *power-law* for the total-degree *CCDF* of the property graph with exponents that lie in $[0.65, 2.05]$.

Moreover, to obtain a more accurate picture regarding the morphology of each schema, we distinguish between arcs for which transitivity holds (i.e., subsumption relationships) from the others (user-defined properties). This is not the case in [8] which mixes both kinds of arcs.

Furthermore, the percentages of schemas exhibiting each of the features under consideration are different (see Figure 1). This fact further justifies the decision to study individual schemas rather than the universal *SW* graph. In this context, the main contributions of this work are:

i) This is the first work analyzing the *property* graph for individual *SW* schemas We show that in their majority they approximate a *power-law* for property total degree functions (94.8% for *VR* and 67.2% for *CCDF*). In contrast to our work, [9] studied only the subsumption graph of schemas, while [8] did not distinguish subsumption relationships from user-defined properties.
ii) By analyzing the subsumed classes *VR* (apart from the *CCDF* which has been also analyzed by [9]), we have realized the high variability of number of subsumed classes values (beyond the high variability of their frequencies). More precisely, we show that the *VR* (resp. *CCDF*) function approximates a *power-law* for the 87.9% (resp. 60.2%) of the schemas defining a significant number of classes. Unlike our work, [9] studied the universal subsumption graph ag-

[1]With the term "individual schema" we refer to the union of the schema under consideration and the schemas it relies on.

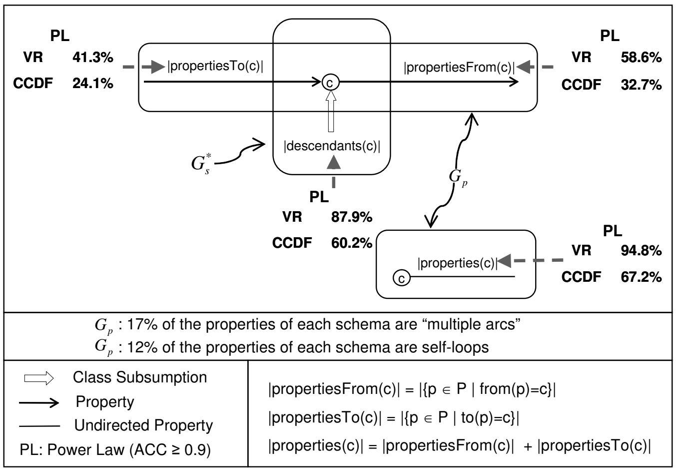

Fig. 1. The main results of our analysis

gregating a set of taxonomic schemas (i.e. schemas with few or no properties) and reported a *power-law* exponent equal to 2.2. In our work, we have found that individual schemas approximate a *power-law* for subsumed classes *CCDF* (resp. *VR*) with exponents that lie in $[0.54, 1.47]$ (resp. $[0.97, 2.44]$).

iii) We provide the means to sketch an abstract morphology of *SW* schemas. In particular, we show that the classes with big degrees in the property graph (i.e., classes with many properties) are usually located at the higher levels of the subsumption graph. Finally, class subsumption hierarchies are mostly unbalanced with large branches and many leaves (i.e., 75% of the classes). To the best of our knowledge, no other work has reported similar results.

The knowledge of the above features is essential for guiding synthetic *SW* schema generation. This is actually a first step towards synthetic *SW* data generation (instantiating one or several *SW* schemas) needed to benchmark *SW* repositories and query languages implementations against voluminous datasets. Our choice is motivated by the fact that the full potential of the *SW* lies on the existence of schemas, which can be exploited to support advanced querying and reasoning services against the available *SW* data. Last but not least, existing work in the literature already reports experimental findings regarding *SW* data ([10], [11], [12], [7], [13], [14], [15]).

The remainder of this paper is organized as follows: Section II provides formal definitions of *SW* schema graphs, while Section III defines *power-law* distributions. Section IV details the corpus of schemas used in this work, the methods adopted in the experiments performed, and details the results of our analysis. Based on these measurements section V sketches the general morphology of *SW* schemas. Section VI shows how the graph features that are commonly exhibited by real *SW* schemas can be used to generate synthetic ones. Finally, Section VII resumes related work and Section VIII summarizes the contributions of our paper and identifies issues for future research.

II. SEMANTIC WEB SCHEMA GRAPHS

SW schemas are usually represented as directed labeled graphs where nodes are classes or literal types and arcs are properties. These graphs may have self-loops (representing recursive properties) and multiple arcs (when two classes are connected by several properties). In particular, *SW* schemas have two different kinds of arcs. The first comprises attributes or relationships among classes, which are called *properties*. The second comprises *subsumption* relationships (*rdfs:subclassOf*) among classes. As the interpretation of these two arc kinds is different, for each *SW* schema we need to define two graphs: a) the *property* and b) the *subsumption* graph. Both graphs have the same set of nodes (i.e., the union of classes and literal types used in the schema) but they comprise different kinds of arcs.

Def 2.1: The *property graph* of a schema is a directed graph $\mathcal{G}_p = (\{C \cup L\}, P)$, where C is a set of nodes labeled with a class name, L is a set of nodes labeled with a literal type, P is a set of arcs of the form $\langle c_1, p, c_2\rangle$ where $c_1 \in C$, $c_2 \in C \cup L$, and p is a property name.$\diamond$

If $\langle c1, p, c2\rangle$ is an arc, we shall write $domain(p) = c1$ and $range(p) = c2$.

Def 2.2: The *class subsumption graph* of a schema is a directed graph $\mathcal{G}_s = (C, P_s)$, where C is a set of nodes labeled with a class name and P_s is the transitive and reflexive binary relation that represents subsumption relationships among classes.$\diamond$

We can denote an arc of this kind by $\langle c_1, c_2\rangle$ meaning that c_1 is a subclass of c_2.

For example, Figure 3 depicts the property and the subsumption graph of the schema $ns1$ illustrated in Figure 2.

It should be stressed that, according to the RDF/S semantics [16], class subsumption is a transitive relation and hence the subsumption graph should be transitively closed. The effect of the subsumption to the property graph is implicit.

A. Tackling OWL Characteristics

In this work we ignore the logic-style descriptions (e.g., *minCardinality*, *differentFrom* etc.) of schemas expressed in *OWL* [2], apart from those that concern the morphology of their graphs, i.e., *unionOf*, *intersectionOf*, *someValuesFrom*, *allValuesFrom* and *inverseOf* expressions. In particular, we have transformed *OWL unionOf* and *intersectionOf* expressions (in class or property definitions) as depicted in Figure 4. More precisely, for each expression of the from $A \cup B$, $A \cup B \cup C$, $A \cap B$, $A \cap B \cap C$, we have added the appropriate subsumption relationships of the form $\langle A \cup B, \textit{rdfs:subclassOf}, A \cup B \cup C\rangle$, $\langle A \cap B \cap C, \textit{rdfs:subclassOf}, A \cap B\rangle$. We also exploited the *Restriction* feature of *OWL* (*someValuesFrom* / *allValuesFrom*) to identify the domain/range of properties. Finally, *inverseOf* expressions have been taken into consideration by the analysis of total degrees of the property graph (see Section IV-B).

B. Schema Reusability & Refinement

The articulation of SW schemas spread all over the world (through *reuse* or *refinement*) impacts the resulting subsumption and property graphs. Schema *reuse* or *refinement* are well-known notions in the software engineering community and have been widely used for XML schemas [17]. Reusability of *SW* schemas is mainly achieved through the definition of properties, i.e., a schema can define as domain/range of one of its properties a class that is defined in another schema. This case is depicted in Figure 2 where schema *ns4* defines that property p2, which is defined in *ns1*, has as domain the class B2 (defined in *ns2*) and as range the class C4 (defined in *ns4*). Refinement of *SW* schemas is achieved through the introduction of *subsumption* relationships between

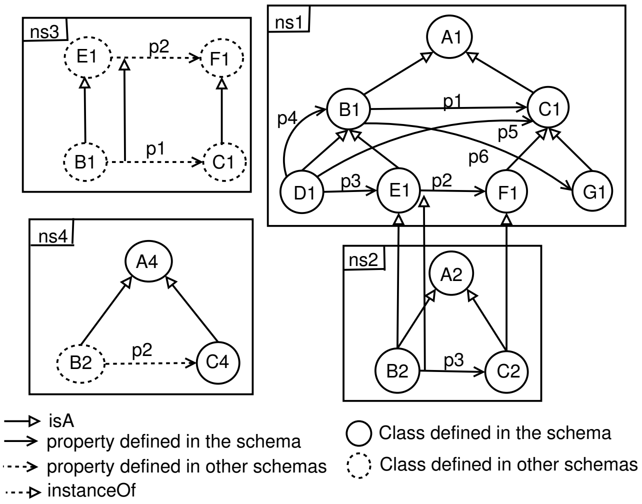

Fig. 2. *SW* schemas reusability and refinement

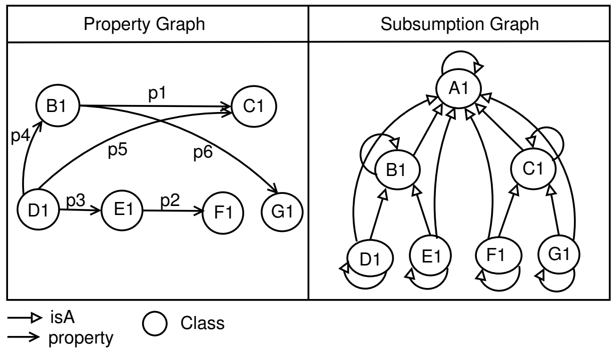

Fig. 3. Property and subsumption graphs of schema ns1 of Figure 2

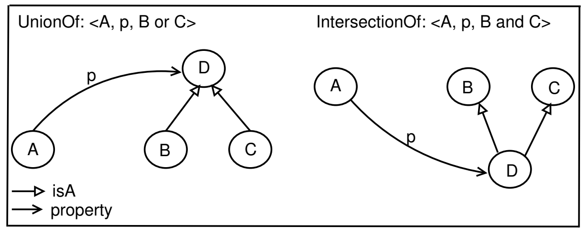

Fig. 4. Treatment of union and intersection OWL constructs

classes/properties defined in different schemas. For instance, in Figure 2, *ns2* defines classes B2 and C2 and declares that they are subsumed by E1 and F1 respectively, which have been introduced in schema *ns1*. Note that a schema can declare that one class may subsume another without defining any of these two classes. For example, *ns3* declares that classes B1 and C1, which are defined in *ns1*, are subclasses of E1 and F1 respectively, which are also defined in schema *ns1*. Due to the aforementioned interconnection among schemas, the (property or subsumption) graph of a schema is obtained from the union of its classes and properties with those of the schemas that are reused or refined by it.

III. Power Laws

In this Section we introduce *power-law*s and elaborate on various kinds of distributions that one can study in order to identify them. Subsequently, we show how we can decide whether a function approximates a *power-law*.

A. Power Law Functions

Def 3.1: A power-law is a function $f : X \subseteq R_*^+ \rightarrow R_*^+$ of the form: $f(x) = \alpha x^{-\beta}$, where α, β are constants, with $\alpha, \beta \in R_*^+$. Equivalently, $\log f(x) = \log \alpha - \beta \log x$. $\diamond$

This means that $f(x)$ can be drawn as a line in the *log-log* scale with a slope equal to $-\beta$. Power-law functions are *scale-free*, in the sense that if x is rescaled by multiplying it by a constant, then $f(x)$ would still be proportional to $x^{-\beta}$.

The above definition excludes the value $\beta = 0$, since in this case $f(x)$ would be equal to α for all values of x, i.e. f would be constant (uniform distribution, if f is the probability density function of a discrete random variable). Loosely speaking, uniform distributions can be regarded as a trivial case of *power-law* distributions. Intuitively, the value of β is a measure of the skewness of the distribution, i.e. $\beta = 0$ implies no skewness. As will be explained in Section VI, the *power-law* exponents for the distributions studied in this paper can be employed to synthetically generate realistic *SW* schema graphs.

At this point, the question that naturally arises is on what kind of distributions one could investigate *power-law*s. Let X be a Discrete Random Variable (*DRV*) whose set of possible values is denoted by D. For X one could study:

- its complementary cumulative probability density function (*CCDF*), i.e., $P(X \geq x)$;
- the relationship among the values of its range and their rank in decreasing order (*VR*), i.e., a function[2] $VR : [1, |D|] \rightarrow D$.

To measure the occurrence frequency of X values, one could instead consider *PDF* (Probability Density Function), i.e., $P(X = x)$. However, *CCDF* yields more credible experimental results as we will explain in Section III-B. As a matter of fact, one needs only to measure *CCDF* and the results regarding *PDF* follow immediately.

It is worth mentioning, that *VR* reflects the variability of the values, while *CCDF* measures only the occurrence frequencies of the values and not their correlation [18]. To highlight their difference, consider the following example. Let $S = \langle 10, 9, 9, 9, 5, 5, 5, 5, 4, 4 \rangle$ be a sequence of X values. The first and second columns of Table I show respectively the corresponding *PDF* and *CCDF*. For instance, $P(X \geq 4) = \frac{10}{10} = 1$, since 10 elements of S are greater than or equal to 4. Similarly, $P(X \geq 5) = \frac{8}{10} = 0.8$. One could also define a function g (see the third column of Table I) that measures only the discrete values of S that are greater than or equal to a specific value. For example, $g(4) = 4$, since there exist only 4 (i.e., $\{10, 9, 5, 4\}$) distinct values of S which are greater than or equal to 4. Similarly, $g(5) = 3$, since only 3 distinct values of S are greater than or equal to 5. Obviously, g is different from *CCDF*. Consider now that $S' = \{10, 9, 9, \mathbf{8}, 5, 5, 5, 5, 4, 4\} \neq S$. Then, $P(X \geq 4) = 1$ for both S and S', while $g(4) = 4$ for S but $g(4) = 5$ for S'. Table I (right) shows the *VR* function corresponding to S. Specifically, the greatest value of S is 10. Similarly, the second greatest (distinct) value of S is 9. As one can easily observe, *VR* is the inverse of g. As a consequence *VR* is directly correlated with

[2]Although, in the literature *VR* is referred as distribution (e.g. "degree-rank distribution" in [3]), it ignores the occurrence frequencies of values (its definition is referred as non-stochastic in [18]). To refer to both *CCDF* and *VR* with one term, we hereafter use the term "function".

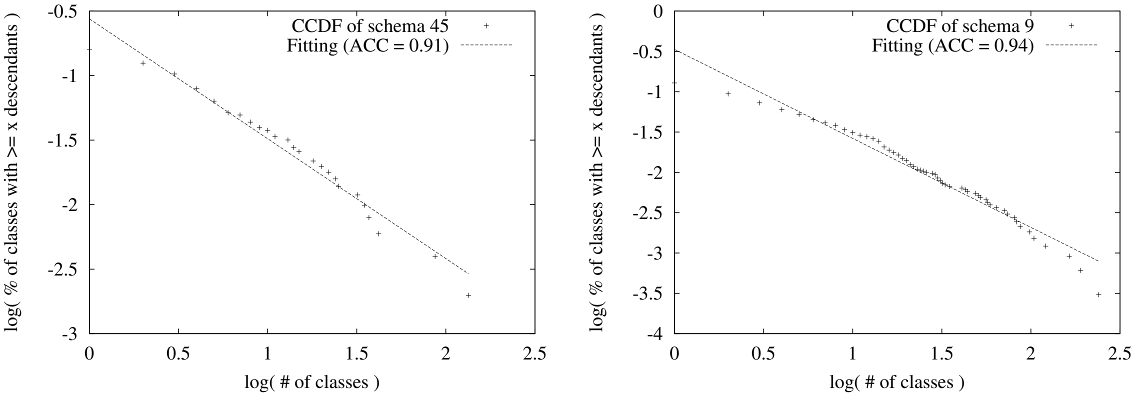

Fig. 5. Examples of different ACC values for *CCDF*

x	***PDF*** $P(X = x)$	***CCDF*** $P(X \geq x)$	$g(x)$
4	0.2	1	4
5	0.4	0.8	3
9	0.3	0.4	2
10	0.1	0.1	1

rank	***VR*(rank)**
1	10
2	9
3	5
4	4

TABLE I
FUNCTIONS CORRESPONDING TO THE BAG $S = \{10, 9, 9, 9, 5, 5, 5, 5, 4, 4\}$

g and not with *CCDF* and hence we measure it separately.

We should also stress that the rank in *VR* refers to a decreasing ordered set of values. For instance, in $\{10, 9, 5, 4\}$ value 10 has rank 1 and value 9 has rank 2. In this respect, the so called Zipfian distribution [19] is different from *VR*. In particular, the former correlates the *occurrence frequency* of values, with their corresponding rank (and thus is also called "frequency-rank" relationship [20]) in decreasing order. For example, the occurrence frequencies of S values in decreasing order consist of the set $\{4, 3, 2, 1\}$, since the most frequent in S value (i.e. 5) has occurrence frequency 4, i.e., $fr(1) = 4$. Similarly, the second most frequent in S value (i.e. 9) has occurrence frequency 3, i.e., $fr(2) = 3$. Since "frequency-rank" relationship is essentially the same as *CCDF* (and *PDF*) [21] we do not measure it separately.

Intuitively, the fact that the *VR* of a *DRV* X follows a *power-law* reveals the high variability of X values. For instance, the value variability of $\{1000, 100, 10, 1\}$ is higher than that of $\{4, 3, 2, 1\}$. On the other hand, the fact that the *CCDF* follows a *power-law* reveals the high variability of the frequencies of X values. For instance, the variability of value frequencies of $\{4, 3, 3, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1\}$ is higher than that of $\{4, 4, 3, 3, 2, 2, 1, 1\}$ (note that in both cases the set of values is the same, i.e., $\{4, 3, 2, 1\}$).

As a consequence, the increased percentages (that are reported in Sections IV-B, IV-C) of the schemas that approximate a *power-law* for *VR* in contrast to *CCDF*, reveal that the high variability of the considered *DRV* values is more frequent than the high variability of their frequencies. Last, but not least, both *CCDF* and *VR* functions are useful (each one for different reasons) for synthetic SW schema generation, as will be explained in Section VI.

B. Power Law Investigation Method

In this paragraph we address the issue of investigating whether a function approximates a *power-law* and if it does, to what extent. We rely on a commonly used method, called Linear Regression [22], to fit a line in a set of 2-dimensional points (based on the least square errors method) and, thus, to investigate whether the *log-log* plot of a function approximates a line. The accuracy of the approximation is indicated by the correlation coefficient, the absolute value of which (hereafter called ACC) always lies in $[0, 1]$. An ACC value 1.0 indicates perfect linear correlation, i.e., the points are exactly on a line. In the sequel, whenever we say that a function approximates a *power-law*, we mean that $ACC \geq 0.9$, i.e., over 90% approximation. To provide a graphical representation of what the value of ACC means, Figure 5 illustrates two functions (figures are plotted in *log-log* scale with log base 10). In the left plot $ACC = 0.91$, while in the right $ACC = 0.94$[3].

If *PDF* follows a *power-law* with exponent β, i.e., $P(X = x) = \alpha x^{-\beta}$, then *CCDF* follows a *power-law* with exponent $\beta - 1$, i.e., $P(X \geq x) = \gamma x^{-(\beta-1)}$ (see [23] for details). Based on this fact, we only study *CCDF* and the results regarding *PDF* immediately follow. In this manner we avoid biased slope computations for the *PDF* plots due to their characteristic 'heavy tails' [18], [23].

IV. EXPERIMENTAL RESULTS

In this section, we present in detail our sampling, methodology and the results of our experimental analysis[4]. In particular, we study the degree distributions of $\mathcal{G}_p$ and $\mathcal{G}_s$.

The out-degree of $\mathcal{G}_p$ can be regarded as the distribution of property domains, while the in-degree as the distribution of their ranges. However, from a conceptual modeling viewpoint, the direction of the properties is not important. One can replace the property $\langle B1, p1, C1\rangle$ of $ns1$ of Figure 2, with the property $\langle C1, p7, B1\rangle$ by inverting the direction and changing the property label (see also the *OWL inverse properties*). Thus, it is reasonable to also study the total-degree distribution of $\mathcal{G}_p$ and try to compare its characteristics with those of the in-/out-degrees.

Furthermore, since subsumption plays a significant role in *SW* schemas we are also interested in investigating the in-/out-degree (corresponding to transitive subclasses/superclasses

[3]To produce the plots as well as to perform linear regression we used Gnuplot.

[4]To perform this analysis we extended VRP [24] statistics package.

id	Name	# of Classes	# of Prop.
1	tap	6031	379
2	dcd100	5112	355
3	not-galen	3135	484
4	opencycprotege	2966	1317
5	cyc	2731	1193
6	bsr	2724	1770
7	milo	2480	458
8	sweet_data	2036	205
9-16	sweet_phenomena	1923	190
17	clib-core-office	1352	1786
18-26	mds	856	914
27	weap_of_mass_destr	828	263
28	ontology	823	296
29-36	science	790	301
37	sumo	643	254
38	framenet_1.1_inferred	537	753
39	adw	445	161
40	p3p-rdf-schema	422	379
41	akt-refont-20020509	362	243
42	kimo	341	126
43	akt_portal_ont	228	208
44	mgedontology	226	114
45	spacenamespace	224	143
46	resume	217	119
47	phontology	193	148
48	spase_051214	176	224
49	cerif	164	226
50	geo_Inf_Met	158	335
51	copyright_Ontology	155	117
52	georelations	148	144
53	onto	115	190
54-55	geocoordsyst	113	102
56	moviedatabase	108	394
57	datatypes	101	334
58	cononto_Fuzzy	101	117
59	unspsc84-title	16518	20
60	unspsc	9810	16
61	go	7006	25
62	acm-css	1483	16
63	mygrid-reasoned	1012	99
64	gams	795	16
65	facc	620	16
66	mygrid-services-lite	592	30
67	java_ontology	503	28
68	mygriddomainontology	463	30
69	sweet_hum_act	295	24
70	sweet_mat_thing	295	24
71	orel	288	56
72	math_inter	223	16
73	kmi_basic	216	17
74	wine_ontology	166	33
75	food_ontology	166	33
76	substance	138	16
77	gold	129	24
78	sweto_v2_3	127	85
79	earthrealm	125	16
80	property	125	16
81	openmath	107	16
82	pizza_20041007	101	46
83	sweet_biosphere	100	16
Small sized schemas reused/refined by others			
84	Dublin Core Element Set v1.1	41	71
85	Dublin Core Terms Namespace	41	71
86	The DCMI Types namespace	53	71
87	FOAF RDF vocabulary	53	127
88	OILStandardSchema	51	35
89	WGS84 Geo Positioning	43	75

TABLE II

83 SCHEMAS WITH ≥ 100 CLASSES (58 WITH ≥ 100 PROPERTIES AND 25 WITH < 100 PROPERTIES)

respectively) distributions of the subsumption graph, $\mathcal{G}_s$. To summarize we consider four *DRV*s, i.e., three for the out-/in-/total-degrees of $\mathcal{G}_p$, and one for the in-degrees of $\mathcal{G}_s$. For each of the two functions of the considered *DRV*s we mainly focus on two aspects: a) the fraction of schemas that approximates a *power-law*; and b) the ranges of the *power-law* characteristic exponents.

A. SW Schemas Corpus

We collected 250 schemas from RDFSuite[5], SchemaWeb[6] and Swoogle [25] schema registries. It should be noted that this corpus contains the biggest (in terms of number of classes and properties) schemas published on the *WWW* until May 2006, including the largest schemas from Swoogle2005 ontology set (with 4000 ontologies). The size of each schema (i.e., the number of classes and properties) is crucial for our analysis since for small schemas the 'noise' would be significant and thus would hinder the deduction of credible conclusions.

For instance, consider a schema that defines 30 properties. On average, there will be many classes that appear as domain of one and only property, i.e., the corresponding nodes of $\mathcal{G}_p$ will have out-degree equal to 1. Some other classes will have out-degree 2 and only few classes will have a significantly higher out-degree (e.g. 10). Then the out-degree *CCDF* plot consists of 3 points (i.e., $P(X \geq 1)$, $P(X \geq 2)$ and $P(X \geq 10)$). Since two points always define a line, the third point will probably not decrease the ACC value significantly. In this manner, almost all plots would be considered as good approximations of a *power-law* and as a consequence our study would loose its interest. To avoid this effect, the plots should comprise many points and this is achieved only for schemas with a significant number of properties (for plots that correspond to $\mathcal{G}_p$) or classes (for plots that correspond to $\mathcal{G}_s$).

Hence, we categorized (see Table II) the schemas of our corpus according to their size. One group consists of 83 schemas with more than 100 classes. Note that there are four sets (i.e., $9-16$, $18-26$, $29-36$, $54-55$) of strongly interconnected schemas (i.e., each schema of a set reuses/refines all the other set schemas). A second group (subset of the first one) comprises 58 schemas that have more than 100 properties. It should be stressed that our extended corpus of 250 schemas also contains (e.g. schemas 84-89 in Table II) schemas that are smaller in size (but popular nevertheless), such as *FOAF* and *Dublin Core*. As they are small, they have not been analyzed separately and as a consequence the results of our analysis do not refer to them. Note however, that their classes and properties affect the results regarding many other big sized schemas that refine/reuse them. In this respect, for each schema we consider the graph obtained as the union of itself and all the schemas that it reuses or refines (see Section II-B). Detailed figures depicting the distributions of all corpus schemas are available at http://athena.ics.forth.gr:9090/RDF/VRP/SWSchemas/.

B. Features of the Property Graph

In this paragraph we present the results of our experimental analysis regarding $\mathcal{G}_p$. Apart from in-/out-/total-degrees, we also study the percentage of self-loops and multiple arcs. The main conclusion drawn is that the majority of *SW* schemas approximate

[5]http://athena.ics.forth.gr:9090/RDF/VRP/Examples/

[6]www.schemaweb.info

Domains (out-degrees)		
Function	≥ 100 **Properties**	≥ 300 **Properties**
CCDF	19/58 (**32.7%**)	9/30 (**30%**)
VR	34/58 (**58.6%**)	20/30 (**66.6%**)
Ranges (in-degrees)		
Function	≥ 100 **Properties**	≥ 300 **Properties**
CCDF	14/58 (**24.1%**)	12/30 (**40%**)
VR	24/58 (**41.3%**)	22/30 (**73.3%**)
Total (in- and out-degrees)		
Function	≥ 100 **Properties**	≥ 300 **Properties**
CCDF	39/58 (**67.2%**)	25/30 (**83.3%**)
VR	55/58 (**94.8%**)	29/30 (**96.6%**)

TABLE III
NUMBER OF SCHEMAS EXHIBITING A POWER-LAW FUNCTION FOR DOMAIN/RANGE/TOTAL

Distr.	Min	Max	Mean	St.dev.	COV
self-loops	0.0	0.382	0.126	0.124	0.984
multiple arcs	0.0	0.626	0.177	0.194	1.09

TABLE IV
DISTRIBUTION OF SELF-LOOPS/MULTIPLE ARCS

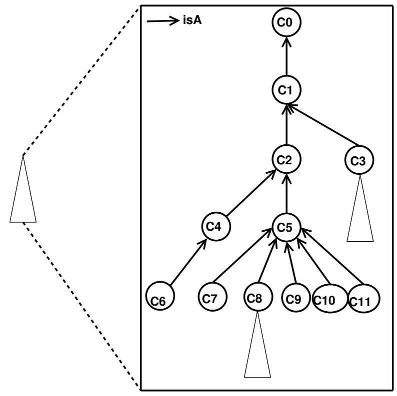

Fig. 6. Structural pattern of class hierarchies

Function	≥ 100 **Classes**	≥ 200 **Classes**
CCDF	50/83 (**60.2%**)	48/61 (**78.6%**)
VR	73/83 (**87.9%**)	59/61 (**96.7%**)

TABLE V
NUMBER OF SCHEMAS EXHIBITING A POWER-LAW DISTRIBUTION FOR CLASS DESCENDANTS

a *power-law* for total-degree functions, while for out- and in-degrees the corresponding percentages are significantly lower. We should also note that the percentages of the *VR* are always higher (see Table III) than those of the *CCDF*. This fact reveals that the variability of degree values is higher than the variability of their frequencies. In other terms, the trend of schema properties to define as domain/range focal (i.e., of high degree values) rather than peripheral (i.e., of low degree values) classes is stronger than the trend of schemas to define much more frequently peripheral than focal classes.

1) Distribution of Property Domains (out-degrees): Table III (upper) shows the portion of schemas that define more than 100/300 properties and also approximate a *power-law* for each considered function of *property domains*. The main conclusion that can be drawn is that the *VR* functions of property domains of most schemas (i.e., 58.6%) approximate a *power-law*. For *CCDF* the range of exponents lies between $[0.5, 1.99]$, while for *VR* it lies between $[0.83, 2.22]$.

2) Distribution of Property Ranges (in-degrees): Table III (middle) shows the portion of the schemas that define more than 100/300 properties and also approximate a *power-law* for each function of *property ranges*. We conclude that as the number of properties increases, the portion of schemas that approximate a *power-law* also increases. The range of *CCDF* exponents lies in $[1.12, 1.71]$. Finally, for *VR* the corresponding range of its exponents is $[0.91, 2.23]$.

3) Distribution of Total Degrees: There is a strong correlation between the number of properties that have as domain a class and the number of properties that have as range the same class. This correlation was revealed by the analysis of the total-degree (in- and out-degree) functions, the results of which are shown in Table III (bottom). Note that the percentages for total degrees are greater than those corresponding to both in- (ranges) and out-degrees (domains). So if we consider the properties as undirected, then their distribution better approximates a *power-law*. The range of the exponents in this case lie in $[0.65, 2.05]$ for *CCDF* and in $[0.79, 2.18]$ for *VR*.

4) Self Loops and Multiple arcs: As we can see in Table IV, the percentage of self-loops is quite significant, i.e., 12.6% in the average case and its maximum reaches the 38.2% for schema 37. The average percentage of multiple arcs is slightly bigger, i.e., 17.7%, but its maximum roughly diverges from that of self-loops, reaching the 62.6% for schema 56.

C. Features of the Subsumption Graph

Concerning $\mathcal{G}_s$, we mainly focus on the in-degree (i.e., class descendants) functions[7]. To discover dominating structural patterns of these hierarchies, we also studied the percentage of schema classes that are leaves. In addition to the vertical view of the hierarchies provided by the *DRV* for in-degrees and the percentage of leaf classes, we employ another *DRV* for analyzing the number of classes located at each hierarchy level and thus, reveal a horizontal view of the subsumption hierarchies.

From our experiments we observed that class hierarchies are usually unbalanced, i.e., some branches are very deep, while others are shallow. Thus, few classes located high in the subsumption graph have big in-degree (i.e., many descendants), in contrary, most of those located at lower levels have small in-degree. In particular, large branches expose few leaves at the medium levels, while most of them are located at the maximum branch depth (see Figure 6). In conjunction with the list-like structure [27] of subsumption relationships, we can sketch the general morphology of class hierarchies as depicted in Figure 6 (transitive arcs are not drawn for simplicity).

1) Distribution of Class Descendants (in-degrees): Table V shows the portion of schemas that approximate a *power-law* for the two functions (*CCDF* and *VR*). Our results are presented for two groups of schemas: one with ≥ 100, and another with ≥ 200 classes. We can easily observe that the emergence of a *power-law* is almost total for *VR* function. Also, by comparing the two columns of Table V, we can observe that, as the number

[7]For the analysis of out-degree (i.e., class ancestors) functions, readers are referred to [26].

Distr.	Min	Max	Mean	St.dev.	COV
% of leaf classes	49.88%	96.37%	74.41%	0.1	0.14

TABLE VI
DISTRIBUTION OF PERCENTAGES OF LEAF CLASSES

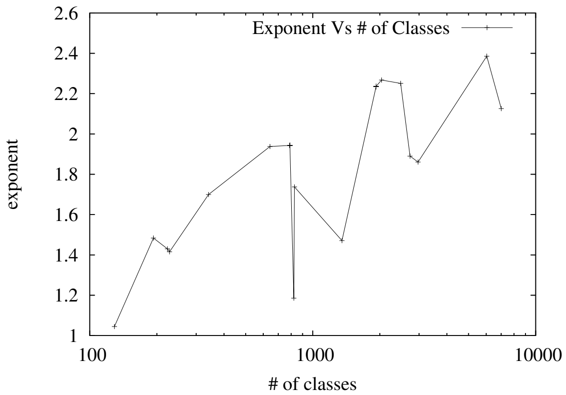

Fig. 7. Exponents vs number of classes for *VR* class level distribution

of classes increases, the portion of schemas that approximate a *power-law* for both functions, also increases. The range of *CCDF* exponents lies in $[0.54, 1.47]$ with a non linear but increasing trend with respect to classes number. The range of the *VR* exponents lies in $[0.97, 2.44]$, while their mean value is 1.4 approximately.

As one can easily observe from Table V, the percentages of the *VR* are higher than those of the *CCDF*. In this case, every *DRV* value corresponds to the number of (transitive) subclasses of one or more classes. The variability of values is high, since classes located at higher levels in the hierarchy have much more subclasses than classes located at lower levels. It is evident, that this variability increases as long as the total depth of the class hierarchies increases. On the other hand, the value frequencies (and consequently their variability) heavily depends on the morphology of hierarchies.

2) Leaf Classes: We observed that on average 75% of the classes of each schema are leaves (see Table VI). Given that in most schemas subsumption hierarchies are deep (on average $depth = 8$ [26]), if the number of direct descendants was the same for all classes, the percentage of leaves would be close to 50% (i.e., as in complete trees). However, from our experiments we observed that this number is small for intermediate level classes and big for the classes that are close to the leaves (see Figure 6).

3) Distribution of Class Levels: We consider that the level of a class c equals 0 if c is the root, otherwise it equals $p + 1$ where p is the level of its parent class (if c has more than one parents, then p is the maximum of their levels). In most cases, the number of classes at each level is different (so *PDF* is a constant function, i.e., $P(X = x) = \frac{1}{depth}$ for all possible x values). The biggest number of classes is observed between the middle and the maximum leaf level. This is due to the fact that only few branches reach the maximum depth of the hierarchies, while most of them end few levels higher.

The class levels *VR* of 42.1% of schemas (for schemas with more than 200 classes it reaches the 54%) approximate a *power-law* with exponents in $[1.04, 2.38]$. Moreover, the corresponding exponent of the *VR* distribution increases as long as the number of classes increases (see Figure 7).

D. Combinatoric Features

An interesting finding of our experiments is that most properties have as domain, classes which are located high in the class hierarchy, i.e., somewhere between the root and the middle level. This was revealed by computing for each schema the correlation coefficient (in most cases in $[-1, -0.5]$) between the depth in $\mathcal{G}_s$, of each class with its corresponding out-degree in $\mathcal{G}_p$. This fact shows that the specification of a class in *SW* schemas is used more for classification purposes rather than for refining classes with additional properties. The same trend was observed for range classes, although the dominance of classes located higher over those located lower in the subsumption graph is not so important as for property domains.

V. EMERGING MORPHOLOGY OF SW SCHEMAS

Figure 8 depicts the abstract morphology of the graphs employed by the SW schemas of our corpus. The upper left part of the figure illustrates the distribution of classes to the various subsumption hierarchy levels. The upper right part of the figure shows the distribution of properties according to their level, computed as the mean of the levels of the classes that it connects (i.e., $level(p) = (level(from(p)) + level(to(p)))/2$).

The drawings of Figure 8 (which resemble vases and amphoraes) were derived by first splitting the range of levels [0...maxDepth] into 4 equally sized intervals (named A, B, C, D), and then counting the classes/properties that are located at each level interval.

At the upper left part of the figure we can observe that the minimum number of classes does not occur at level A (as one would expect) but between A and B. This is due to the fact that level A comprises all the literals, as well as, the classes of commonly reused schemas (like the Dublin Core or the FOAF schema) with shallow class hierarchies. The maximum number of classes is not placed at level D (as one would expect) but at level C (see also Section IV-C.3). This is due to the fact that class hierarchies are mostly unbalanced.

At the upper right part of figure we can see that the maximum number of properties are placed at level B (see also Section IV-D) and the minimum at level D. Notice that the number of properties at level A is bigger than the corresponding number of classes, since top level classes, although few, usually expose several properties.

The bottom part of the figure illustrates the total number of elements (classes and properties) located at each level interval. In particular, the bottom right part of the figure captures schemas that have more properties than classes. For those schemas, the maximum number of properties is bigger than the maximum number of classes for a specific level interval and as a consequence the bottom right part of the figure converges to that of properties (upper right part).

On the other hand, schemas with much more classes than properties are divided into two groups with respect to the level interval, denoted by M, at which the sum of classes and properties reaches its maximum. The former comprises schemas for which M converges to the level interval where the maximum number of classes occurs (resulting in the bottom left part of the figure). The latter comprises schemas for which M converges to the

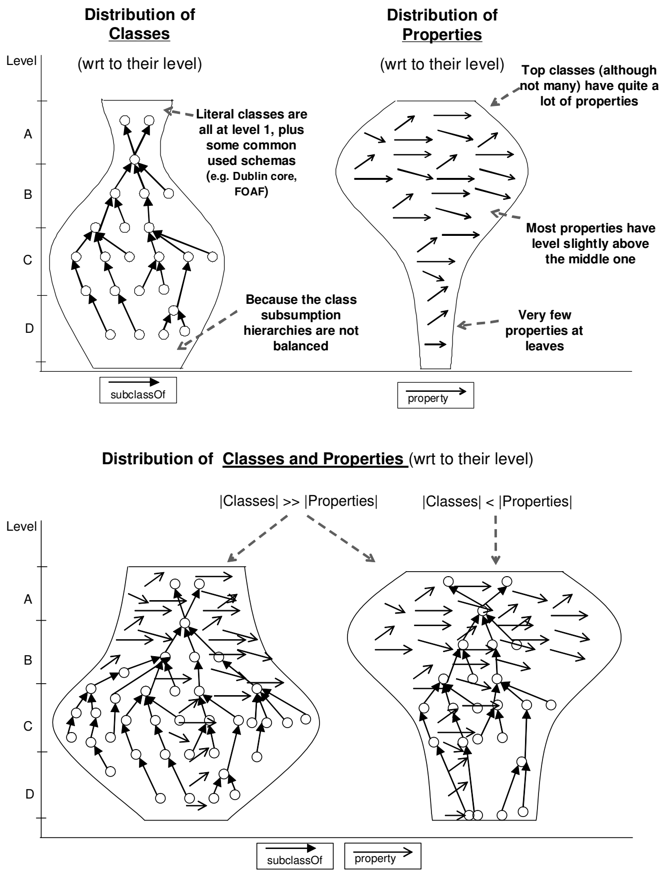

Fig. 8. Distributions of classes and properties w.r.t. their level in the subsumption hierarchy

level interval where the maximum number of properties occurs (resulting in the bottom right part of the figure). M actually depends on the morphology of the subsumption hierarchy of each schema, i.e., its depth, as well as, the percentage of its classes placed at lower levels.

VI. Towards Synthetic SW Schema Generation

In this Section we discuss how our findings can be exploited for generating synthetic *SW* schemas (for more details see [28]) by giving as input:

i) the number of schema classes and properties;
ii) the characteristic *power-law* exponent of the class descendants *CCDF*;
iii) the characteristic *power-law* exponent of the total-degree *VR*;
iv) the maximum depth of the class subsumption hierarchy;
v) the morphology of the subsumption graph, e.g. on average 75% of classes are leaves and the level at which most classes are located is on average $\frac{3}{4}$ of the depth of the subsumption graph;
vi) the fact that classes of high out-degree in the property graph are located highly in the subsumption graph.

We should notice that one may generate a taxonomy, i.e., a schema comprising only (or mainly) subsumption relationships (e.g., schemas $59-83$ in Table II). In that case, we only need to generate $\mathcal{G}_s$ and the inputs (iii) and (vi) are useless.

The generation algorithm consists of two steps. The first, exploits the aforementioned findings in order to reduce the generation of $\mathcal{G}_p$, $\mathcal{G}_s$ to the problem of generating graphs given their in- and out-degree sequences[8] (for $\mathcal{G}_s$ the arcs transitivity should be taken into consideration). The second step is to solve that problem by a *Linear Programming* reduction, which allows us to generate *SW* graphs in polynomial time. Bellow, we sketch the main aspects of synthetic schema generation algorithm, with special focus on the manner in which the findings of this work are exploited.

A. Generating $\mathcal{G}_p$, $\mathcal{G}_s$ Degree Sequences

To generate the total-degree sequence of $\mathcal{G}_p$, as well as the in-degree sequence of $\mathcal{G}_s$, we exploit two methods to sample a bag of values from a *DRV* that follows a *power-law* [28]. The first (denoted by *PDFSampling*) is based on the *PDF*[9] of the *DRV*, while the second (denoted by *VRSampling*) is based on the *VR* function of the *DRV*. *PDFSampling* is useful when we know the maximum allowed value for X. This is actually the case of in-degrees of $\mathcal{G}_s$ in which the maximum allowed value is $|C|-1$ (i.e., root descendants). On the other hand, *VRSampling* is useful when we know the sum of the values that should be sampled. This is actually the case of the total-degrees of $\mathcal{G}_p$ where the sum of all total-degree values should be twice the number of schema properties (graph arcs). Recall that in the total-degree sequence we count every arc twice, i.e., once through the origin and once through the destination node.

1) The case of $\mathcal{G}_p$: In order to generate $\mathcal{G}_p$, we will first generate its *total-degree* sequence, denoted by D. We choose to generate D instead of $Dout$, i.e., out-degree sequence and Din, i.e., in-degree sequence, because the percentage of real *SW* schemas that approximate a *power-law* for the *total-degree VR* is higher (i.e., 94.8%) than the corresponding percentage for *out-* (i.e., 58.6%) and *in-degrees* (i.e., 41.3%). Given the characteristic exponent, we can generate D by using the $VRSampling$ method.

Moreover, the strong correlation (see Section IV-B) between the out- and in-degrees of nodes can be used to split D into Din and $Dout$.

2) The case of $\mathcal{G}_s$: To generate the in-degree sequence of $\mathcal{G}_s$, we can exploit the fact that the majority (i.e., 60.2%) of schemas approximate a *power-law* for *class descendants CCDF* function (see Table V). Given a) the characteristic exponent, b) the depth (denoted by d) of $\mathcal{G}_s$, and taking into account that on average the 75% of classes of real *SW* schemas are leaves (see Table VI), we can generate the *in-degree* sequence of $\mathcal{G}_s$ by using the $PDFSampling$ method. To generate the *out-degree* sequence of $\mathcal{G}_s$, the best choice is the *class levels* distribution, whose *VR* function approximates a *power-law* for 42.1% of schemas (see Section IV-C.3). In this respect, we can generate the *out-degree* sequence of $\mathcal{G}_s$ by using the $VRSampling$ method. To this end, we also exploit the finding that the level, denoted by k, at which the maximum number of nodes are located is approximately $\frac{3}{4} \times depth$ for real *SW* schemas (see Section V). The number of classes located at other levels decreases as long as the distance of the specific level to level k increases.

[8]The (in-/out-/total-) degree sequence of a graph is a sequence comprising the (in-/out-/total-) degree of every node.

[9]As mentioned in Section III-A the *PDF* exponent equals the *CCDF* exponent plus the unity.

B. Generating $\mathcal{G}_p$, $\mathcal{G}_s$ given their degree sequences

At this step we assume that the degree sequences of $\mathcal{G}_p$, $\mathcal{G}_s$ are given. We can generate $\mathcal{G}_p$, $\mathcal{G}_s$ by a *Linear Programming* reduction. In particular, candidate arcs can be expressed as variables and the degree sequences as linear constraints. The arcs transitivity (needed only for $\mathcal{G}_s$) can also be modeled by a set of linear constraints.

Since the generation of each graph is a separate process, we need a method to map one node of $\mathcal{G}_s$ to one and only node of $\mathcal{G}_p$. To this end, we exploit the fact that nodes with high out-degree in the $\mathcal{G}_p$ are located highly in the $\mathcal{G}_s$ (see Sections IV-D, V). In this manner, we achieve that both two graphs have the same set of nodes.

Finally, we should consider attributes i.e., arcs of $\mathcal{G}_p$ which have as destination *Literals* (e.g., String, Integer). We add to the set of $\mathcal{G}_p$ nodes, the Literal types, as specified in *XML schema*[10]. Then we connect them to the pre-existent nodes of $\mathcal{G}_p$ under the condition that the total-degree sequence of $\mathcal{G}_p$ remains the same. The percentage of attributes over the total number of properties is given as input.

VII. Related Work

In this section we discuss the contributions of our work with respect to prior research in the field. The results presented in this paper go beyond the statistical analysis presented in [29], which provides only min/avg/max values for depth and size of *RDFS* class (and property) subsumption hierarchies. Moreover, authors in [27] analyzed the expressiveness of the *OWL* fragments employed by a large corpus of *SW* schemas (we employee the same corpus of schemas but analyze only the big ones) and discovered that only few *OWL* schemas are *OWL* Full, while most of them are *OWL* Lite or DL. Furthermore, [9] classified the ontologies of the DAML ontology library[11] into three clusters, the taxonomic (i.e., ontologies with few properties and a large number of classes), the logic-style (i.e., ontologies with a high number of axioms per class) and the database-like one (i.e., ontologies of medium size containing on average 65 classes and 25 properties). They observed that the distribution of the DAML restrictions (e.g., property cardinalities) follows a *power-law* for each of the 3 clusters. They also observed that the class descendants *CCDF* approximates a *power-law* (with exponent 2.2) for the taxonomic cluster. However, they did not study the property graph. Moreover, according to the analysis presented in [8], the total-degree *CCDF* of the graph obtained by aggregating all ontologies of the DAML library approximates a *power-law* (with exponent 1.48). However, authors did not distinguish between subsumption and user defined properties, which constitutes a decisive factor for the quality of the analysis method and the interpretation of the presented results. Unlike that study, in our work we treat and analyze the graphs of each *SW* schema *separately* (i.e., the graphs obtained from the union of its classes/properties and only those of other schemas that it reuses or/and refines).

Additionally, a recent work [30] analyzed the graph structure of two *OWL* ontologies (one of them is schema 37 while the other is a small one) focusing on measures like the diameter, the density of the graphs as well as on different notions of centrality (i.e., degree, betweenness, eigenvector centrality). They showed the usefulness of these measures for the identification of important concepts, of clusters of concepts and of the core conceptual backbone of an ontology. In this study both classes and properties have been considered as graph nodes (i.e., a bipartite graph). In the same direction, [31], [32] address the problem of ontology ranking, which is useful in the case that one should choose one among many ontologies returned by a *SW* search engine to a user query (e.g., find a schema that defines a class named "Person"). Specifically, to decide which ontology is better than others, [31] uses various graph measures, such as the number of properties divided by the number of properties and subsumption relationships, the number of attributes divided by the number of classes, the number of instances per class and the ratio of the classes that have instances. Furthermore, as many ontologies may contain a class that matches the user search criteria, [32] tries to estimate to what extent a particular class is representative of the specific ontology. To this end, each class is ranked based on the number of its subclasses, attributes and properties. In addition, the average distance of the shortest paths connecting classes whose label is similar to the search terms is employed. Obviously, [31], [32] do not study the degree distributions of property and subsumption graphs of *SW* schemas. Summarizing, the metrics proposed in [30], [31], [32] are useful for evaluating and ranking ontologies according to various quality criteria. However, this is out of the scope of our work, since we mainly focus on examining graphs features of real *SW* schemas that can be exploited to generate synthetic ones.

Furthermore, there exist works [10], [11], [12], [7], [13] that study features of the data graphs instantiating schemas rather than the schema graphs themselves. Unlike these works, we are interested in features commonly exhibited by *SW* schemas. In particular, authors in [10], [11] collected a voluminous set of online FOAF[12] documents and analyzed the resulting RDF instance graph. They also observed a *power-law* for both in- and out-degree distribution, while authors in [12] analyzed a slice of a specific folksonomy and found that the network composed of the tags from the folksonomy follows a *power-law* degree distribution. Moreover, authors in [13] analyzed subsets of the instance graphs of the Gene Ontology (schema 61) that also exhibit *power-law* degree distributions. Additionally, authors in [7] focused on aspects such as the provenance, the age and the size of *SW* documents (i.e., schema instances). They found that the *CCDF* of instances per class follows a *power-law*, i.e., few classes are populated by many instances while most classes by few instances or none at all. These results provide a complementary view regarding the significance of classes, i.e., not only (as in our work) determined by the number of properties for which they appear as a domain/range, but also by the corresponding number of instances. However, a study of the involved data graphs is not presented in [7].

VIII. Conclusion

To the best of our knowledge, this is the first work that measured and analyzed the graph features of individual schemas coming from an adequately big *SW* corpus. The main conclusions drawn from our analysis are that the majority of schemas with a significant number of classes and properties approximate a *power-law* for class descendants and property total degree distributions.

[10] http://www.w3.org/XML/Schema

[11] www.daml.org/ontologies

[12] www.foaf-project.org/

These findings reveal that there exist few ”focal” classes that form the conceptual backbone of the defined schema, and many ”peripheral” ones that are used to further detail the analysis of the former. When a ”peripheral” class is added to the schema, it is more likely to be related through properties with ”focal” classes rather than with other peripheral ones. Moreover, the ”focal” classes of a schema consist *ideal* articulation points for interconnection with other schemas, since many properties are located in their neighbourhood (the path between a focal concept and the others is small). Both processes of *SW* schemas development fit in the definition of preferential attachment [5] (also called the “rich-get-richer” phenomenon), which has been proven to yield *power-law* degree distributions.

We have already started exploiting the findings of this work for synthetic *SW* data generation [28] as a part of our ongoing *RDF* benchmarking efforts [33].

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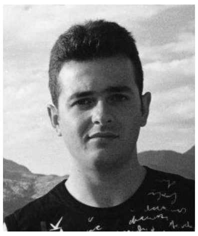

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